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Adaptation of an aridity index for mid-season evaluation of Midwest corn yield

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Adaptation of an aridity index for mid-season evaluation

of Midwest corn yield

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ABSTRACT

A modified aridity index was presented as a risk management tool for assessing possible Midwest corn yields during the growing season. The modifications were the reduction from a monthly scale to a weekly scale and the inclusion of a weighting scheme to account for corn development. Most crop yield models utilize the relationship of yield (percentage of potential) to evapotranspiration (percentage of potential). Sub-monthly indexes involving fairly direct evaluations of evapotranspiration for crop assessment have been developed in the past with satisfactory results. However, the evaluation of actual and potential evapotranspiration for these index computations is not easy to assess in near real-time because some data for input are not readily available (e.g., pan evaporation, net radiation, soil water). The aridity index, which accounts for evapotranspiration indirectly with readily available daily maximum temperature and daily precipitation data, is presented as a near real-time alternative. A model was established on the relationship between the aridity index and corn yield on data from 1980 to 1999. The relationship was tested on the 2000 and 2001 growing seasons and was found useful for evaluating the chance of yield being above or below trend. Because of the usefulness of the aridity index, a way to display it for the Midwest in near real-time was produced.

CHAPTER 1. GENERAL INTRODUCTION

1.1 Introduction

Because of the great economic importance of agriculture, it is favorable to recognize the degree of uncertainty regarding the season's harvest and to plan accordingly. The opportunity to benefit increases as lead-time of reliable information or prediction increases and the range of uncertainty narrows. Consequently, much work has been done to forecast crop yield. Walker (1989) reviewed the two main techniques of crop modeling, the simulation approach and the regression approach. Studies done with simulation models (e.g., Duchon 1986) require numerous details about crop management and environment. For yield estimation over a large area, the regression approach has been more widely used (Walker 1989). Because of the importance of moisture to crops and the harmfulness of limited moisture, it is natural to relate crop yield to the occurrence and severity of drought, which is usually expressed in terms of an index. Taylor (personal communication 2002) explains, "In order for index data to be a useful indicator for risk assessment, it must be simply derived and indicative of a result. The index concept is not intended to be rigorously predictive, but is expected to provide reliable assessment of risk and detection of risk change." Byun and Wilhite (1999) provide a summary of some drought indexes to preface their discussion of the advantages and disadvantages of the indexes:

> Most drought indexes are based on meteorological or hydrological variables. They include the Palmer Drought Severity Index (PDSI; Palmer 1965), Rainfall Anomaly Index (RAI; van Rooy 1965), deciles (Gibbs and Maher 1967), Crop Moisture Index (CMI; Palmer 1968), Bhalme and Mooly Drought Index (BMDI; Bhalme and Mooly 1980), Surface Water Supply Index (SWSI; Shafer and Dezman 1982), National Rainfall Index (RI; Gommes and Petrassi 1994), Standardized Precipitation Index (SPI; McKee et al. 1993, 1995), and Reclamation Drought Index (RDI; Weghorst 1996). The Soil Moisture Drought Index (SMDI; Hollinger et al. 1993) and Crop-Specific Drought Index (CSDI; Meyer et al. 1993; Meyer and Hubbard 1995) appeared after CMI. ... Of all the indexes, the PDSI is still the most widely used and recognized index on an operational basis (Byun and Wilhite 1999).

The popularity of the PDSI and CMI promotes uses, such as crop assessment, for which they were not intended (Meyer et al. 1993a), and in some situations prove to be quite unreliable (Meyer et al. 1991).

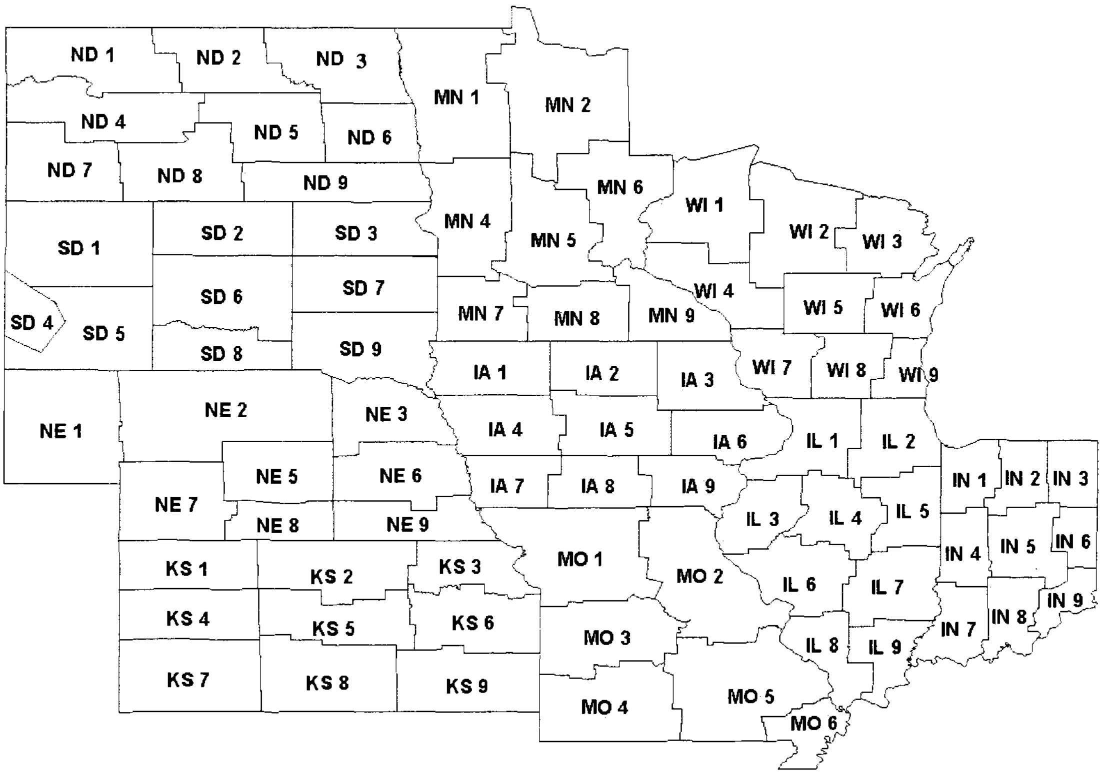


Figure 1.1 Midwest climate and crop districts

The following work provides the basis for applying the adapted aridity index described in this study to a sub-state level; namely climate/crop districts in several Midwest states (Figure 1.1). A monthly drought index computed by Walker (1989) is an example of an index perhaps better suited for regressions related to wheat yield. Walker (1989) observed a highly correlated relationship between the historical drought index and Canadian wheat yield, which he used to forecast 1987 Canadian wheat yield with the frequently updated drought index. As a step in separating the influence of weather from the influence of technology, Thompson (1986) presented a crop-weather model that related corn yield to preseason precipitation (September through June), June temperature, July precipitation, July temperature, August precipitation, and August temperature. Stephens et al. (1994) plotted a monthly weighted rain index against Australian district wheat yield. Because they were interested in wheat yield for all of Australia, they weighted each station's monthly rain according to the contribution percentage of the district to the total Australian wheat crop. Stephens et al. (1994) weighted the monthly rain according to its importance for the crop and made adjustments for soil moisture in drought or flooding situations. The index had a strong relationship to the average Australian wheat yield and Stephens et al. (1994) indicated that if the seasonal rainfall could be predicted accurately (such as with the Southern Oscillation), wheat yield assessment would be improved. Harouna and Carlson (1994) presented a monthly aridity index and evaluated Iowa corn and soybean trend adjusted yield against both July and August index values. Except for August, corn yields had the highest correlation to the aridity index when compared against July and August heat stress (Carlson 1990) and against July and August soil moisture levels (Shaw 1983). Harouna and Carlson (1994) suspected the correlation differences between the months were related to the crops' needs for varying amounts of water for each stage of development.

Harouna and Carlson's (1994) suspicions agree with Jensen (1968) and Nairizi and Rydzewski (1977) who showed that, for each crop growth stage, there are various yield responses to soil moisture stress. Indeed, this concept was reflected in Stephens' et al. (1994) weighting of monthly rain for Australian wheat and in Thompson's (1986) coefficients on the monthly precipitation terms in his model. Walker's (1989) area weighted drought index was also computed by summing the growth as a function of atmospheric demand and crop phenology.

Crop development, at some points in the life cycle, can advance to the next stage in just several days, so a monthly time scale can smooth the importance of the variable or split a growth stage into two pieces. A smaller time scale is likely to be better suited when dealing with crop growth and yield. Shaw (1983) applied weighting factors in 5-day groups on his daily stress index (SI). Shaw

(1983) defined the stress index such that if corn transpired all the water it needed to maintain optimal growth, and if availability of moisture was sufficient, there was zero stress. The stress values become different from zero as the ratio of corn's actual evapotranspiration to the potential amount needed for maximizing production becomes different from 100 percent. When developing their crop-specific drought index (CSDI), Meyer et al. (1993a) recognized that crop development timing has to be considered when relating yield to drought or stress. The CSDI is also designated as a ratio of actual evapotranspiration to potential evapotranspiration, but crop development timing was incorporated by taking the evapotranspiration ratio to the power of a crop stage coefficient (Meyer et al. 1993a). Both authors reported satisfactory results with their respective indexes.

The yield prediction method by Shaw (1983) works well for Iowa and is founded on solid physical principles. However, the actual and potential evapotranspiration used in the stress index are calculated with measurements of precipitation, pan evaporation, and estimation of crop stage. Therefore, a problem with the method arises because the pan evaporation network density, maintained by the National Climatic Data Center (NCDC) and disseminated through NOAA (National Oceanic and Atmospheric Administration) National Data Center Climate Data Online (NNDC-CDO) (http://cdo.ncdc.noaa.gov/) is not very great across the Midwest (Figure 1.2). For the existing locations, it is possible to assume the pan evaporation at a single station may be representative of its district. However, at least one district in each state for the 2000 and 2001 seasons did not encompass a pan evaporation station, as seen in Figure 1.2, and thus is not conducive for consistent yield predictions across the many Midwest districts. Indeed, there were 8 stations lost and only 2 gained from 2000 to 2001. The yield prediction method by Meyer et al. (1993a) also works well over a range of climate conditions and geographical locations, but complete data acquisition here is also a potential problem. To compute the potential evapotranspiration for the CSDI, the following daily station data are needed, which were assumed to be representative of a crop reporting district (CRD), net radiation, wind, minimum temperature, maximum temperature, and 24-h averaged dew point

(Meyer et al. 1993a). The actual evapotranspiration calculation in the CSDI needs daily precipitation from several stations and soil water data (Meyer et al. 1993a). Meyer et al. (1993a) used growing degree days to indicate when to use the next crop stage coefficient. It was thought that net radiation and soil water data would be troublesome to collect in near real-time and the CSDI would be slightly cumbersome to maintain. Because the evaluation of actual and potential evapotranspiration is not straightforward and is not easy to assess in near real-time, an alternate method is explored in the rest of this study.

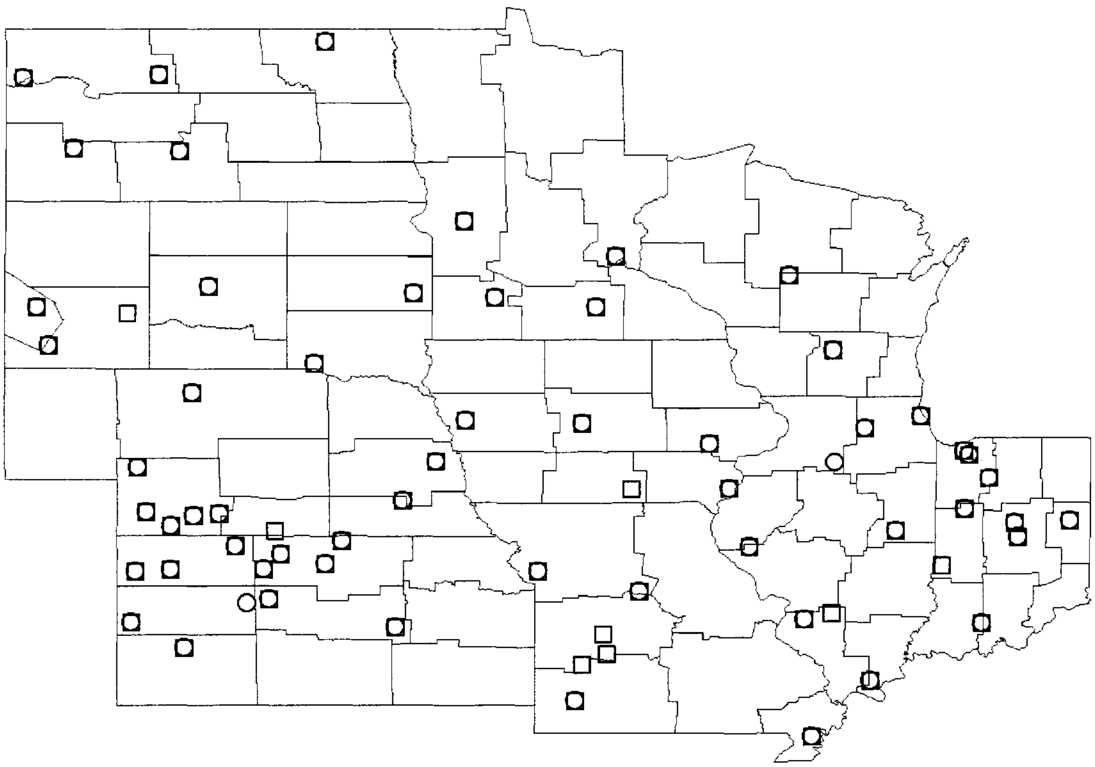


Figure 1.2 Pan evaporation stations for 2000 (square), for 2001 (circle), and for both 2000 and 2001 (square and circle).

With deference to Shaw's (1983) stress index, air temperature plays a large role in evaporation from plants, and precipitation is a major factor for the availability of moisture, so it was thought that they alone could also be used in determining the amount of yield a corn crop will produce. In a general sense, an average amount of precipitation during the growing season (assuming a sufficient initial soil water profile) will provide sufficient moisture for an average corn crop. However, drier and warmer than usual (i.e., arid) conditions will stress the corn crop, which according to Shaw's (1983) stress yield relationship will result in a lower yield. Carlson et al. (1996) used the aridity index from Harouna and Carlson (1994) to confirm that conditions were usually wet and cool, which is favorable for corn (Thompson 1988), when the smooth running average of the Southern Oscillation index was less than -0.8 (El Niño) during the summer. The aridity index by Harouna and Carlson (1994), which uses precipitation and maximum temperature data (that were readily available on a nearly daily basis in 2001), fits well with the concept of crop yield deviating from trend when the weather deviates from average. Its ability to predict corn yield was tested below.

The adaptation of the aridity index made use of some concepts from Shaw's (1983) corn yield prediction program which was based on soil moisture and crop moisture stress. As discussed above, stress does not have a constant influence on the yield during the crop life cycle. In order to resolve the corn phenology, Harouna and Carlson's (1994) aridity index was reduced to a weekly time scale.

1.2 Thesis Organization

The description of the aridity index and its reduction to a weekly scale are detailed in Chapter 2 along with the description of the data. Analysis of the aridity index's relationship to yield is presented in Chapter 3. Results from applying the method to the 2000 and 2001 corn growing seasons for testing are in Chapter 4. Chapter 5 is a discussion about the limitations of the aridity index as it was presented in this study. In Chapter 6, a summary and conclusions are presented.

CHAPTER 2. METHODOLOGY AND DATA SOURCES

2.1 Definition of the Aridity Index (AI)

Harouna and Carlson (1994) used monthly precipitation's normalized departure from average, a technique discussed by Barring and Hulme (1991), and subtracted it from the monthly maximum temperature's normalized departure from average, applied in the same manner, to calculate an aridity index. Such a definition corresponded to positive values for warmer and drier than average conditions, which tend to have a negative effect on corn yield. Although the term "aridity" becomes a misnomer, the index from Harouna and Carlson (1994) was modified (Equation 2.1) so it is the *weekly* maximum temperature's normalized departure from average (Equation 2.2) subtracted from the *weekly* precipitation's normalized departure from average (Equation 2.3).

The index of aridity for each climate week (i) and year (j) is given by (climate week 1 begins March 1 for any given year):

$$AI_{ij} = P'_{ij} - T'_{ij} \qquad (2.1)$$

where

$$T_{ij} = \frac{T_{ij} - \overline{T}_i}{S_{ti}} \qquad (2.2)$$

$$P_{ij} = \frac{P_{ij} - \overline{P}_i}{S_{pi}} \qquad (2.3)$$

T'_{ij} (P'_{ij}) is the standardized weekly average maximum temperature (total precipitation) for week i and year j.

$\overline{T}_i$ ($\overline{P}_i$) is the weekly average maximum temperature (total precipitation) over all years for week i.

T_{ij} (P_{ij}) is the weekly average maximum temperature (total precipitation) for week i and year j.

S_{ti} (S_{pi}) is the standard deviation of the average maximum temperature (total precipitation) over all years for week i.

The index equally weights the contribution of temperature and precipitation and generally gives negative (positive) values when the weather is warm and dry (cool and wet). This definition has the accumulation of weighted negative weekly AI values (discussed below) correspond to low yield. This results in a slope that generally appears positive when yield deviations (discussed in section 2.2.2) are plotted against the weighted weekly AI seasonal sum, and allows users to associate AI less than zero with a decreased chance of good yield.

Shaw (1983) dealt with the yield's response to the timing of stress by implementing a weighting scheme. Since silking time for corn is the most sensitive to stress, Shaw (1983) accordingly weighted stress during silking the most heavily and reduced the weight as the time (in 5-day periods) before and after silking increased. Shaw's (1983) yield prediction method starts with an initial potential yield and subtracts from it as stress accumulates. Thus, yield loss can be assessed during the season by noting the sum of stress values at the particular time. At the end of the season, the summed stress values give a seasonal stress index. These concepts, weighting for phenology and summing the index throughout the season, were incorporated here with the weekly AI. A seasonal AI-yield relationship is different from a seasonal stress-yield relationship because, instead of starting with a potential yield and subtracting for stress, the AI method starts with a predicted yield extrapolated using trend line yield. The initial yield prediction deviates as the weekly AI sum deviates from zero. The weights applied to each week's AI were adopted from Shaw (1983) assuming the critical times for temperature and precipitation deviation from average are approximately the same as the critical times for stress. The seasonal progression of "weighted weekly AI" (AI_n) for weeks i = 11, 12, ..., 27 used for public information is computed by:

$$AI_n = \sum_{i=11}^{n} k_i AI_i \tag{2.4}$$

where k_i is the factor used to adjust for crop phenology at week i (Table 2.1). The value of AI_n can be zero if, for example, a cool and wet week followed a warm and dry week.

Table 2.1 Climate week dates and corn phenology weighting factors.

Climate Week (i)	Begin Date	Weighting Factor (k_i)
11	5/10	-0.5
12	5/17	-0.5
13	5/24	-0.5
14	5/31	0.5
15	6/7	0.5
16	6/14	0.5
17	6/21	1.0
18	6/28	1.0
19	7/5	1.0
20	7/12	1.0
21	7/19	2.2
22	7/26	1.6
23	8/2	1.3
24	8/9	1.3
25	8/16	1.3
26	8/23	1.0
27	8/30	0.75

2.2 Data Sources

2.2.1 Maximum Temperature and Precipitation

Daily precipitation and daily maximum temperature data were obtained from National Weather Service Cooperative Observer Program (COOP) stations disseminated by NCDC through NNDC-CDO (http://cdo.ncdc.noaa.gov/). For a given district, all available stations' daily data were sorted into the appropriate climate week and then averaged over the week and all stations. To standardize a given district's weekly precipitation and maximum temperature values with Equations 2.2 and 2.3, the 30-year (1971 to 2000) averages and standard deviations were used for the particular climate week. The standardized weekly precipitation and weekly maximum temperature were then used in Equation 2.1 to compute AI for all districts shown in Figure 1.1 and for climate weeks 11, which begins May 10, through week 27, which begins August 30 (Table 2.1). After applying weighting, the index was summed over the season (hereafter seasonal AI or AI_{27}).

Attempting to use the method with preliminary work during the summer of 2001, near real-time daily precipitation and daily maximum temperature were downloaded from NCDC (ftp://ftp.ncdc.noaa.gov/pub/data/coop-data/) for some stations (large dots and circles respectively) shown in Figure 2.1. Other stations (small dots) shown in Figure 2.1 were included to illustrate that COOP network coverage would be adequate for weekly AI calculations if most of the stations in Figure 2.1 were included in the near real-time source provided by NCDC . AI values calculated from this data source were similar to the AI values calculated later from the quality-controlled data from NNDC-CDO (http://cdo.ncdc.noaa.gov/). For some weeks, an AI calculation was not possible for such districts as MN 8 and IL 3 where precipitation and/or maximum temperature values were missing for the single station contained in the district. The preliminary work did not include the northern part of the Midwest.

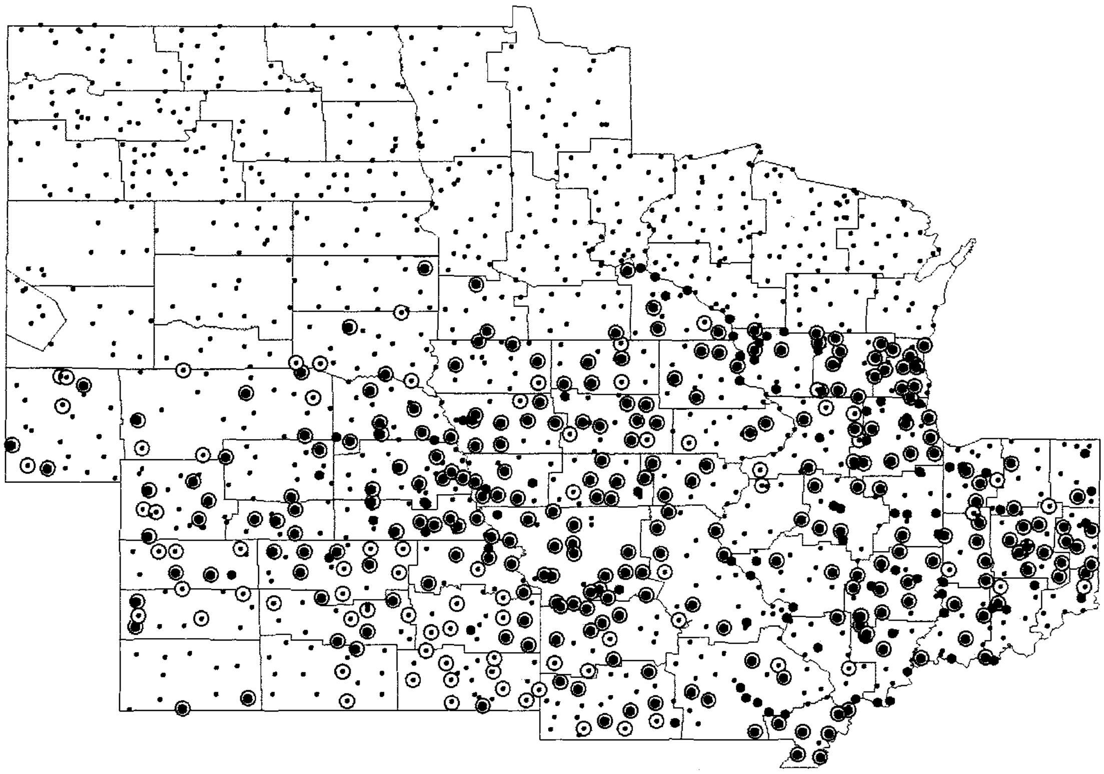


Figure 2.1 COOP stations (small dot), precipitation stations for 2001 (large dot), and maximum temperature stations for 2001 (circle). Note: precipitation and maximum temperature stations shown are valid for week 24, 2001.

2.2.2 Corn Yield Deviation Percentage (YLD)

Corn yield data from the United States Department of Agriculture (USDA) National Agricultural Statistics Service (http://www.nass.usda.gov:81/ipedb/) were used to establish a relationship with AI_n. The USDA data consisted of district bushels $acre^{-1}$ for the period 1980 through 2000. Though it is likely that irrigation costs would have a strong tie to AI, it was assumed irrigated corn yield would have a minimal tie to AI because irrigation overcomes the negative effect of warmer and drier than usual weather. Yields influenced by irrigation were avoided for districts in Kansas (KS), Nebraska (NE), South Dakota (SD), and North Dakota (ND) because non-irrigated yield data sets were available. Yields influenced by irrigation could not be avoided for districts in Iowa (IA), Illinois (IL), Indiana (IN), Missouri (MO), Minnesota (MN), and Wisconsin (WI) because the usually moister conditions in the eastern states means irrigation is used less and therefore a distinction was not made in the yield data. The states for which there was a distinction between irrigated and non-irrigated (KS, NE, SD, and ND; hereafter referred to as the western states) were analyzed separately from the states for which no irrigation distinction was made in the data (IA, IL, IN, MN, MO, and WI; hereafter referred to as the eastern states).

Corn yields have generally been increasing with time, so raw yields should not be compared to AI_n. For each district, linear regression was applied to the 1980 to 1999 yields. The residuals were then expressed as a percentage difference from the trend line. This percentage deviation of yield from the 1980 to 1999 linear trend will hereafter be referred to as YLD. Thus, the seasonal AI for each year, 1980 to 1999, had a corresponding YLD (except for SD from 1980 to 1983 and for ND from 1980 to 1981, for which relevant yield data were not available). Eastern states' YLD were less variable than the YLD for the western states, and could be modeled. Though western states' YLD was not modeled, both regions' AI_{27} and YLD were analyzed.

CHAPTER 3. ANALYSIS

Figures 3.1a and 3.1b show YLD versus seasonal AI for the eastern states and the western states, respectively. Data plots for the extraordinary year of 1993 were included, but were not used for fitting models because, although the 1993 data plots fit with the other years' data plots, they were clearly more variable and would increase the uncertainty of predictions. Even though flooding in 1993 did not affect the entire 10-state area, all 1993 data were left out for simplicity. Average weather is less beneficial to a corn crop with increasing latitude (i.e., too cool), causing the relationship between seasonal AI and YLD to be less consistent. The data for northern districts in MN and WI did not fit well with the curve in Figure 3.1a, but were kept as part of the data set in the interest of broader application of the AI method. However, it was thought that this AI method should not be used for the 3rd district of MN because of the inconsistent relationship of this district's YLD to AI_{27}, so MN 3 was excluded.

3.1 Late Season Relationship of YLD to AI and Application

It was clear from Figures 3.1a and 3.1b that highly negative seasonal AI is harmful to the corn crop because of the arid conditions. In other words, YLD values become increasingly negative as arid conditions persist (increasingly negative AI_n values). Theoretically and similarly, YLD values could become increasingly negative if very cool and wet conditions persist (increasingly positive AI_n values). Though the latter happens less frequently, the scatter on the positive AI_{27} side of the charts in Figures 3.1a and 3.1b support the idea. Average precipitation and average maximum temperatures (AI_n of approximately zero), more often than not, produced YLD above trend. These situations suggest a physically realistic quadratic relationship between YLD and AI_{27}.

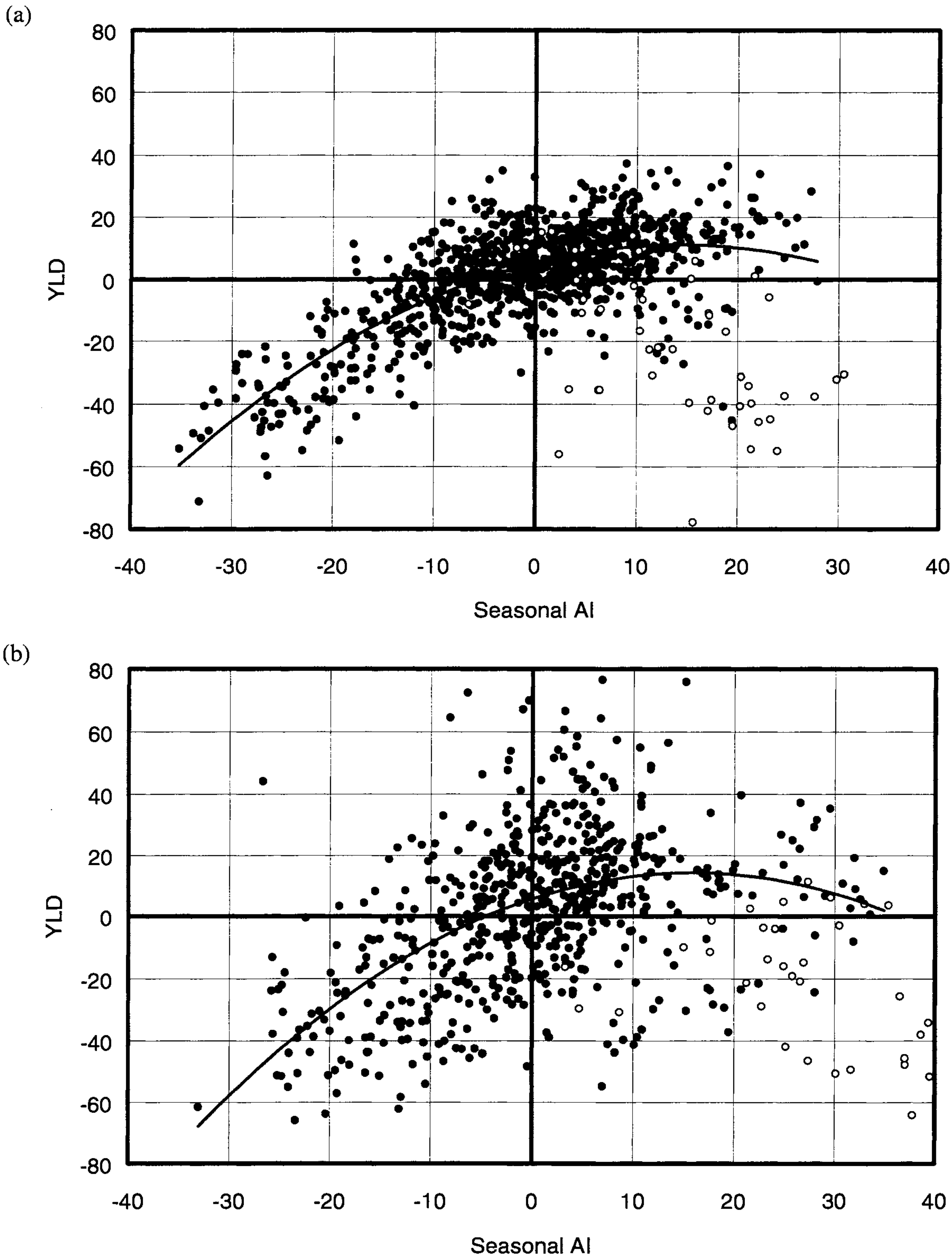


Figure 3.1 YLD versus seasonal AI from 1980 to 1999 for districts in the eastern states (a) and in the western states (b). Thin curved lines are the least squared fits of second order linear regression equations. 1993 was excluded from curve fitting, but plots are included as unfilled circles.

Although better seasonal AI based yield models may exist, only a second order multiple regression model was explored in this study because of the physical basis for such a model. An alternate approach is discussed in Chapter 5. The general multiple linear regression model is given by Equation 3.1 (Ott 1993).

$$\hat{Y} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k + \varepsilon \qquad (3.1)$$

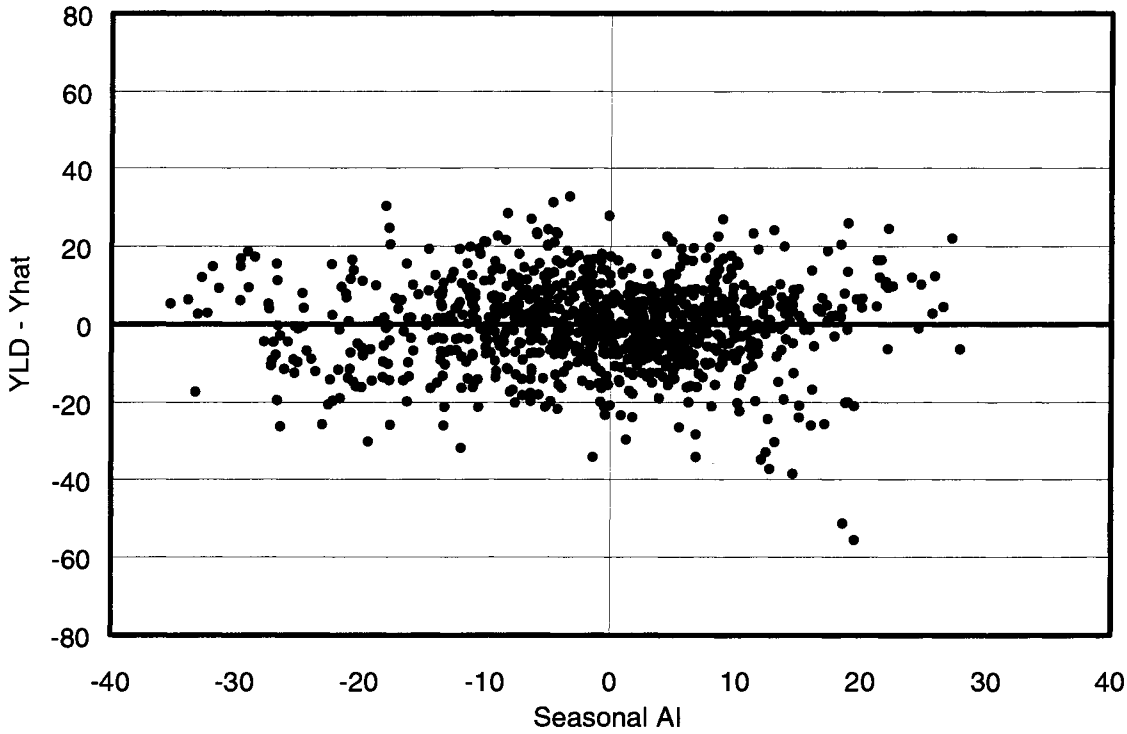
To capture the quadratic relationship between YLD (the dependent variable) and AI_{27} (the independent variable), k = 2, x_1 was substituted with AI_{27}, and x_2 was substituted with $(AI_{27})^2$. Coefficients associated with the curves in Figures 3.1a and 3.1b are shown in Table 3.1 along with the estimated variance of the residuals [$\hat{\sigma}^2_\varepsilon$ where $\varepsilon = YLD - (\hat{Y} \mid AI_{27} = ai_{27})$].

Table 3.1 Coefficient estimates for models plotted in Figure 3.1 and the estimated variance of the residuals. Evidence was sufficient to suggest coefficients were not equal to zero.

Figure	$\hat{\beta}_0$	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\sigma}^2_\varepsilon$
3.1a (Eastern)	5.3382	0.8254	-0.0289	123.01
3.1b (Western)	5.7060	1.0904	-0.0343	506.20

The curve in Figure 3.1b is similar to the curve in Figure 3.1a. The relationship between YLD and seasonal AI was much less consistent for the western states (Figure 3.1b) than it was for the eastern states (Figure 3.1a). This is indicated by the large difference in $\hat{\sigma}^2_\varepsilon$ values in Table 3.1 and the difference in the patterns of residual scatter between Figure 3.2a and Figure 3.2b. For the eastern districts (Figure 3.2a), residual scatter for a given setting of AI_{27} (ε_{AI}) was assumed to be normally distributed (Figure 3.3) with mean 0 and variance $\hat{\sigma}^2_\varepsilon$. The variance $\hat{\sigma}^2_\varepsilon$ was assumed to be constant for all AI_{27} settings and ε_{AI} were assumed to be independent (Ott 1993) though there might be some

(a)



(b)

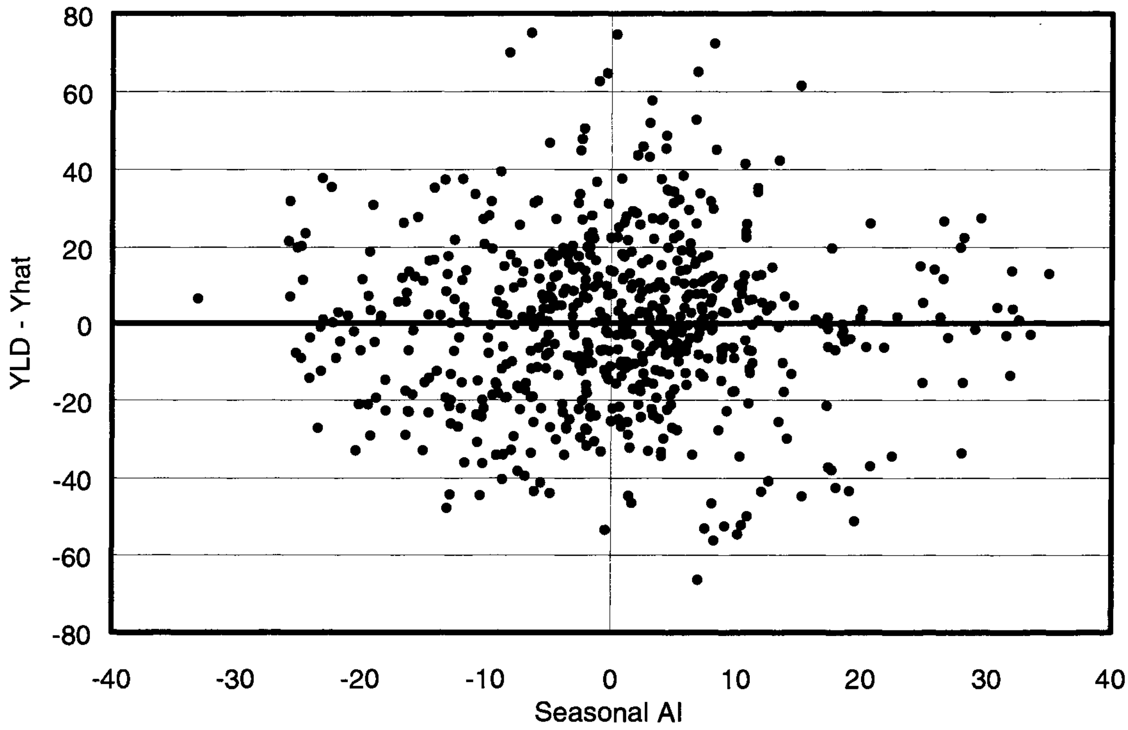


Figure 3.2 Residuals from Figure 3.1a (a) and residuals from Figure 3.1b (b).

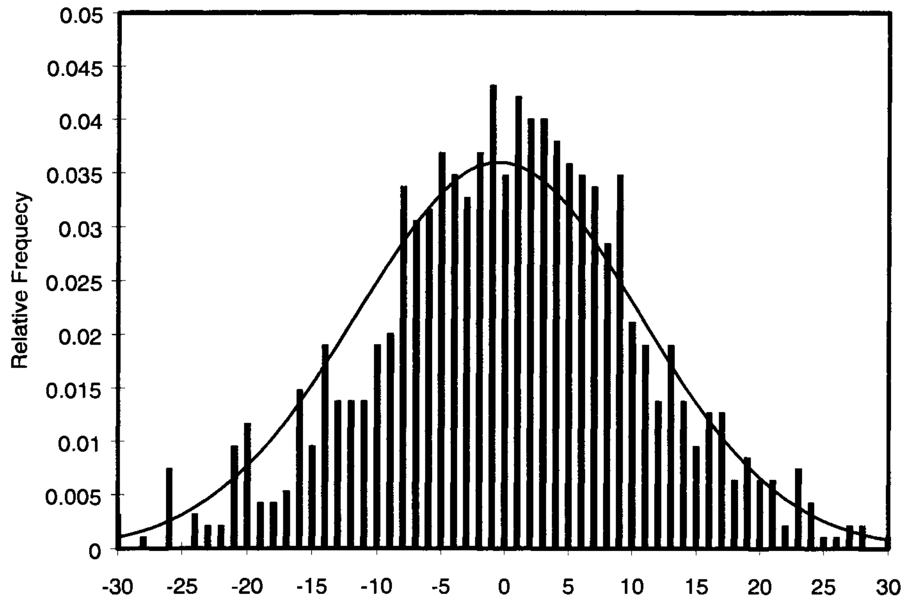


Figure 3.3 Histogram of residuals from Figure 3.2a and Normal curve (line).

spatial dependence (Anderson personal communication 2002). This information can be used to estimate the probability that a particular eastern district YLD will be between arbitrary ranges given an AI_{27} value. The standard deviation for the set of residuals in Figure 3.2b was about twice that of the set of residuals in Figure 3.2a. Thus, it was concluded that the uncertainty of $\hat{Y}$ for western districts was too high to be used with much confidence.

By assuming $\hat{\sigma}_{\varepsilon}^{2}$ is normally distributed, z-scores (Ott 1993) could be used to estimate the probability that a particular YLD would be within the arbitrarily chosen range of ±5 units (a "unit" here is 1 % of the trended yield) of the $\hat{Y}$ value for a given setting of AI_{27}. The z-score for 5 units was 0.4508 (or 5 units is an estimated 0.4508 standard deviations ($\hat{\sigma}_{\varepsilon}$ = 11.1) away from the mean). The corresponding probability for a z-score equal to ±0.4508 is 2*(0.177) or 0.354. This means there is about a 35% chance that actual YLD will be within ±5 units of the value calculated (assuming $\hat{Y}$ is the mean YLD for a given setting of AI_{27}) from the eastern states' model (assembled from the appropriate coefficients in Table 3.1). Compared to modeled YLD, approximately a third of actual YLD values will be over 5 units from the modeled YLD, approximately a third of actual YLD values will be under 5 units from the modeled YLD, and approximately a third of actual YLD values will be within 5 units of the modeled YLD.

The late season application becomes invalid if utilized too early. However, even if an evaluation could only be made at the end of week 27 (September 5), it would still be beneficial because the crop would stand about 2-4 weeks before harvest would begin, which is about September 22 (http://www.lgseeds.com/). If the modeled YLD is accurate enough, this lead-time could be enough to be quite serviceable. Fortunately, because of the importance of moisture during silking, it is quite possible to make valid computations a couple of months before season's end of modeled YLD based on the value of AI_n. This possibility is described in more detail in the next section.

3.2 Sequential Sampling

Of course, the seasonal AI will not be known exactly until the end of the season. Before the end of the season, AI_n tends to be at a particular level and to not vary greatly from then on. Therefore, it is often safe to assume that AI_n will equal AI_{27} (or be at least reasonably close). With consideration to this assumption, which starts to become valid at week 19, YLD can be modeled with AI_n. If AI_n does vary substantially in the last several weeks of the season, it can be tracked because of the weekly scale and the frequent updates. Since AI is determined weekly, modeled YLD can be adjusted with each assessment of AI_n during the season.

A sequential sample is shown in Figure 3.4 for a hypothetical district as an example. The district's actual YLD was compared to AI_n and the modeled YLD (starting at week 19) as they were updated each week. Recall that the AI method starts the predicted YLD at the specific district's trend and is thus zero. When the first weeks of the season were processed, it was seen that the district AI_n was between 0 and 2 and likely beneficial. Little changed in the first five weeks, which means the weekly raw AI was near zero each time and the district was probably experiencing near average precipitation and maximum temperatures. Weeks 16, 17, and 18 were cooler and wetter than average bringing AI_n up to about 8. At week 19, one could begin to anticipate the seasonal AI value, and thus legitimately model the YLD. Until the last 5 weeks of the season, AI_n increased only slightly or remained neutral, then it slowly decreased indicating that the end of the season was warm and dry. In this case, warm and dry was beneficial at the end of the season because of the adequate moisture attained with the positive weekly AI during silking. An end of season evaluation of modeled YLD (+9.6 %) showed good agreement with the actual YLD (+12.6 %). However, an important point to consider is the possibility of assuming no extreme weather would occur (especially during the critical silking and filling periods) after week 18. If this were a reasonably safe assumption, then over two months before the end of the season, it would be quite sensible to assume the district's YLD would have a strong chance to be well above trend based on the modeled YLD (again, assuming AI_{19} will be reasonably close to AI_{27}). There is value in a weekly AI_n assessment even if the weather varies from average because an AI_n tending upward (downward) would indicate an above (below) trend YLD and/or continued gain (loss).

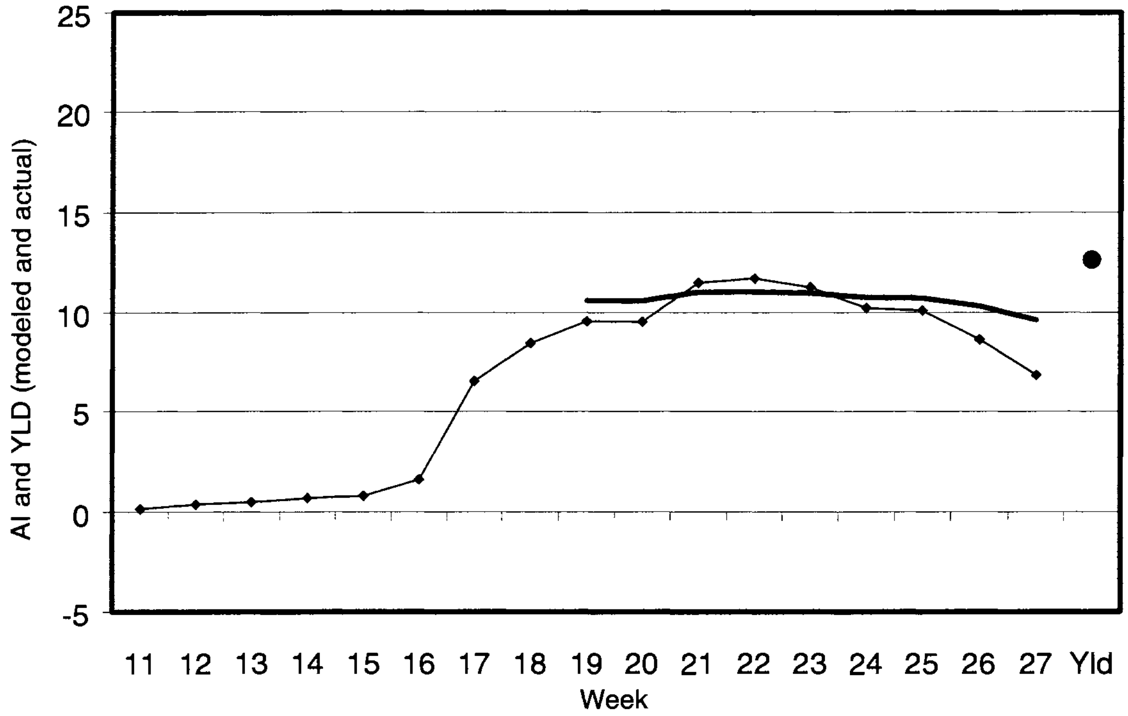


Figure 3.4 Sequential sample for a hypothetical district. AI_n is the diamond marked line, the modeled YLD is the thick line, and the actual YLD is the large dot.

3.3 Early Season Relationship of YLD to AI and Application

At the beginning of the season, AI_n is set to zero. The start from zero, fractional weighting, and tendency for AI components to be near average usually keep the first weeks' AI_n values very small. As a result, the season end relationships seen in Figure 3.1 are not useful early in the season. Until weighting is heavier and AI_n has had a chance to accumulate, such that one can anticipate using the season-end relationship (a week or two before silking week, assumed to be week 21), Tables 3.2 through 3.5 can be used to make AI_n-based evaluations of the crop's potential. Tables 3.2 through 3.5 present the 1980 to 1999 eastern states' district counts of cases with above trend YLD for particular ranges of AI_n. The last column in each of the tables expresses the ratio of the above trend cases to the total as a percentage. Evidence to suggest the percentages on the tables are different than the unconditional chance of being above trend (62.5%) was determined with Equation 3.2, which is the normal approximation to the binomial test statistic (Ott 1993).

$$z = \frac{\hat{\pi} - \pi_0}{\sigma_{\hat{\pi}}} \qquad (3.2)$$

where

$\hat{\pi}$ is a particular percentage from Table 3.2, 3.3, 3.4, or 3.5
π_0 is the unconditional percentage of being above trend (= 0.625)
$\sigma_{\hat{\pi}} = [\pi_0(1-\pi_0)n^{-1}]^{0.5}$ where n is the total cases associated with the particular percentage

If $|z| > z_{\alpha/2}$ ($z_{\alpha/2} = 1.96$ for $\alpha = 0.05$), the hypothesis that a particular percentage is the same as the unconditional percentage ($\pi = \pi_0$) was rejected and the particular percentage was said to be higher than the unconditional percentage if z was greater than zero (‡) and lower than the unconditional percentage if z was less than zero (†).

After the third calculation of AI for the season for all years (week 13: about 2 months before silking), the range for AI_{13} was quite small (Table 3.2). However, some value can be derived from AI_{13}. If AI_{13} is between 0 and +2, there is a better than usual chance to be above trend (69.0%). If AI_{13} went above +2 and was too warm and dry (recall raw aridity was negatively weighted the first three weeks) early in the growing season, the associated probability of an above trend YLD (51.5%) was significantly lower than usual. At week 17 (about 1 month before silking), the range for AI_{17} was still somewhat narrow, but again certain AI values provide some meaning (Table 3.3). When AI_{17} was between 0 and 4, there was a strong likelihood (about 70%) of positive YLD and when AI_{17} was below -2 (except for a few cases with AI_{17} less than -6), there is a likelihood (roughly a 60% chance) of negative YLD.

Although the range for AI_{21} and AI_{25} is large enough for the season end YLD-AI_{27} relationship to be useful, early season methodology, as done with week 13 and week 17, can continue to be helpful. As AI_{21} and AI_{25} (Table 3.4 and Table 3.5, respectively) went below -8 and -10 respectively, more districts had below trend YLD than above trend YLD. Conversely, as AI_{21} and AI_{25} went above 0 and +2 respectively, a large percentage of districts achieved positive YLD.

Table 3.2 For particular AI values, the number of districts in eastern states (1980 to 1999) at week 13 (2 months before silking), the number of districts with positive YLD, and the corresponding percentage. ‡ (†) indicates percentage is significantly (at the 0.05 probability level) higher (lower) than the unconditional percentage of cases above trend ($\pi_0 = 62.5\%$).

AI	**Districts Above Trend**	**Total (n)**	**% Cases above Trend ($\hat{\pi}$)**
-6 to -4	11	20	55.0
-4 to -2	77	122	63.1
-2 to 0	189	324	58.3
0 to 2	267	387	‡ 69.0
2 to 4	50	97	† 51.5

Table 3.3 Same as Table 3.2, but at week 17 (1 month before silking).

AI	Districts Above Trend	Total (n)	% Cases above Trend ($\hat{\pi}$)
-8 to -6	4	6	66.7
-6 to -4	36	103	† 35.0
-4 to -2	72	148	† 48.6
-2 to 0	156	242	64.5
0 to 2	193	264	‡ 73.1
2 to 4	99	141	70.2
4 to 6	30	40	75.0
6 to 8	4	6	66.7

Table 3.4 Same as Table 3.2, but at week 21 (silking).

AI	Districts Above Trend	Total (n)	% Cases above Trend ($\hat{\pi}$)
-20 to -18	0	1	
-18 to -16	0	2	AI less than -10
-16 to -14	0	10	† 4.6
-14 to -12	0	20	
-12 to -10	3	32	
-10 to -8	13	51	† 25.5
-8 to -6	19	49	† 38.8
-6 to -4	46	84	54.8
-4 to -2	80	120	66.7
-2 to 0	85	130	65.4
0 to 2	96	135	‡ 71.1
2 to 4	84	107	‡ 78.5
4 to 6	74	85	‡ 87.1
6 to 8	42	53	‡ 79.2
8 to 10	16	22	
10 to 12	20	25	AI greater than 8
12 to 14	9	16	73.2
14 to 16	5	5	
16 to 18	2	3	

Table 3.5 Same as Table 3.2, but at week 25 (1 month after silking).

AI	Districts Above Trend	Total (n)	% Cases above Trend ($\hat{\pi}$)
-32 to -30	0	2	
-30 to -28	0	7	
-28 to -26	0	4	
-26 to -24	0	18	AI less than -12
-24 to -22	0	10	† 7.1
-22 to -20	0	19	
-20 to -18	0	14	
-18 to -16	0	8	
-16 to -14	2	14	
-14 to -12	6	17	
-12 to -10	8	44	† 18.2
-10 to -8	29	59	† 49.2
-8 to -6	35	54	64.8
-6 to -4	39	65	60.0
-4 to -2	45	64	70.3
-2 to 0	49	72	68.1
0 to 2	53	78	67.9
2 to 4	71	83	‡ 85.5
4 to 6	66	84	‡ 78.6
6 to 8	50	60	‡ 83.3
8 to 10	43	51	‡ 84.3
10 to 12	30	37	‡ 81.1
12 to 14	27	35	77.1
14 to 16	10	16	
16 to 18	10	13	AI greater than 14
18 to 20	10	10	‡ 82.0
20 to 22	6	6	
22 to 24	5	6	

CHAPTER 4. RESULTS

4.1 Testing Late Season Model Application on 2000 Growing Season

Based on the analysis and model equation for the eastern states, YLD were predicted for 2000 using the 2000 seasonal AI values. Figure 4.1 shows the 2000 seasonal AI, the modeled YLD for the eastern districts, and the actual YLD. The highly negative actual YLD in the western districts generally correspond to the white and light gray areas (where seasonal AI was less than zero) while most of the darker gray districts (where seasonal AI was greater than zero) had positive YLD. Figure 4.2 shows the model error for each appropriate district. Good agreement between modeled and actual YLD occurred for the eastern two thirds of IA, central IN, and central IL. Modeled YLD for districts IA 1 and IA 4 were noticeably lower than the rest of the IA districts' estimates, but were still predicted to be above trend when actually the YLD were below trend. The northeast four districts of IA had reasonably consistent overestimation. Modeled YLD values for the southern tier of IA districts were about 10% above trend. For southwest IA, 10% above trend was a substantial overestimate, but modeled YLD for the other two districts of the southern tier had fair agreement with actual YLD. The model predicted YLD of greater than 7.5% above trend for all of WI. It was suspected that conditions were too cool and wet in WI for YLD to be substantially above trend, so predicted YLD were overestimates. Similar overestimates occurred in northeast IL and northern IN, again possibly from being too cool and wet. MN had both overestimates and underestimates because actual YLD increased from east to west, but AI_{27} decreased from east to west. Actual YLD for southern IL and southern IN were very large. Modeled YLD has a maximum because of the quadratic nature of the model. Seasonal AI for southern IL and southern IN were in a range where modeled YLD were near the maximum. Therefore, it wasn't possible for modeled YLD to be near the actual YLD. Out of 50 eastern districts, 21 had modeled YLD come within ±5 units of the actual YLD.

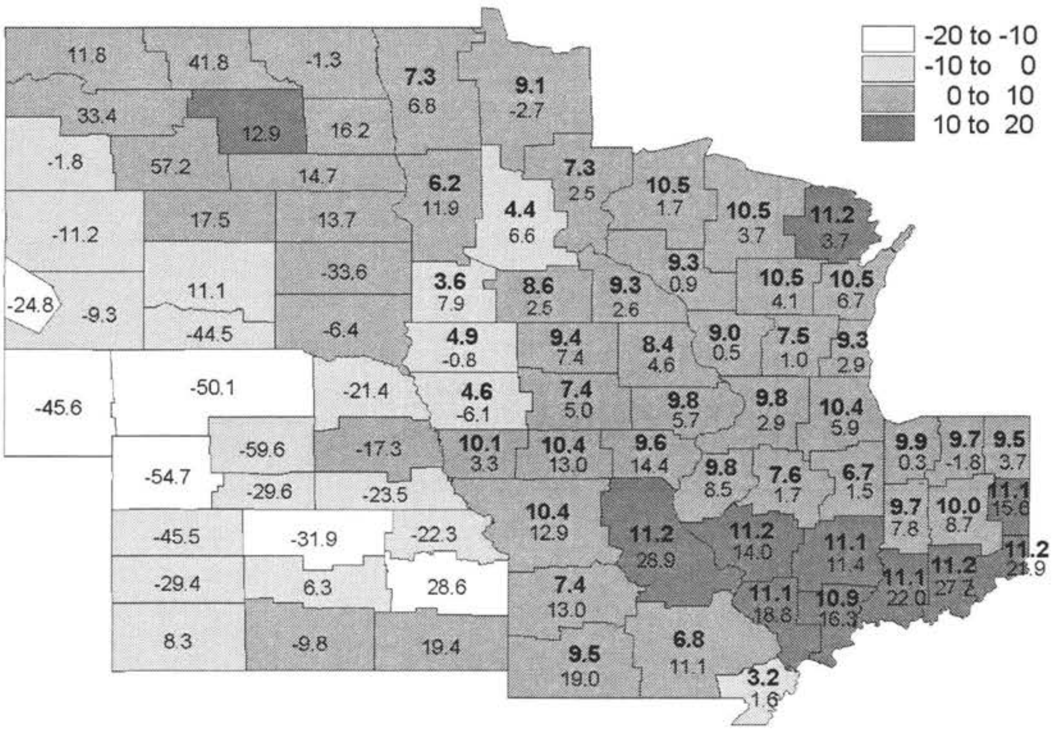


Figure 4.1 District seasonal AI (shaded at intervals of 10 units), actual YLD (small text), and modeled YLD (large bold text) for 2000.

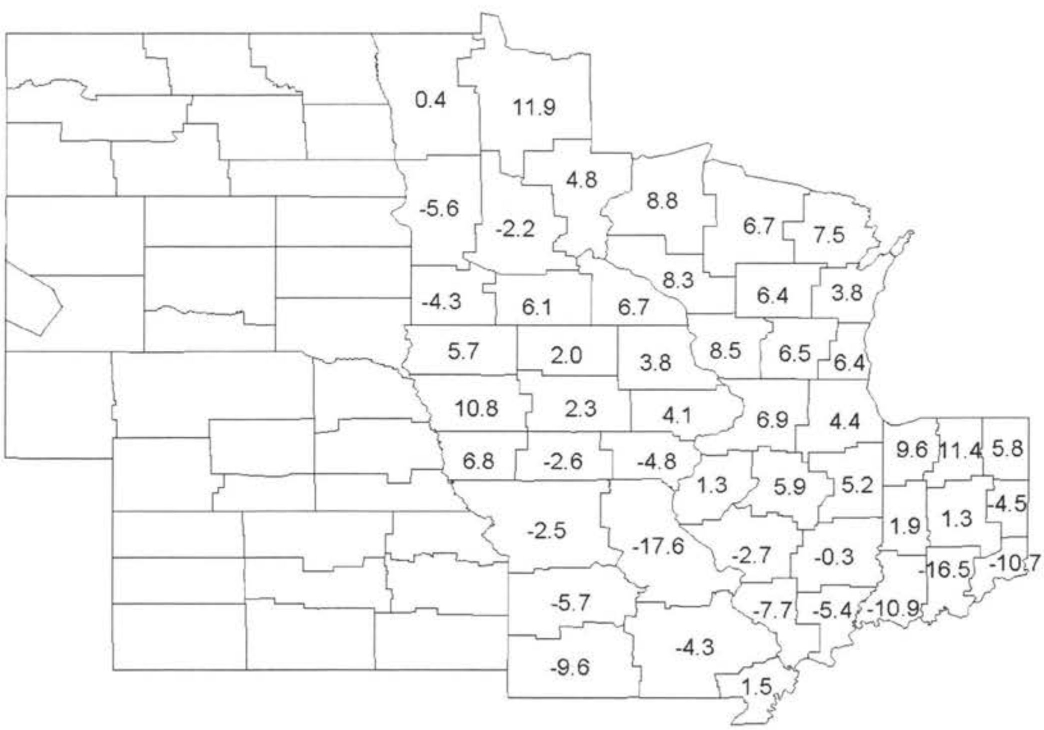


Figure 4.2 Model error (modeled YLD - actual YLD) for 2000.

A plausible rule of thumb for the AI-YLD relationship is a one-to-one proportion, even for the western states. Sign agreement between seasonal AI and YLD was much more common than seasonal AI and YLD having opposite signs. In Figure 3.1a (3.1b), for sign agreement, there are 385 (236) plots in the upper right quadrant and 267 (186) in the lower left quadrant while the opposite sign quadrants, the upper left and the lower right, had only 207 (103) and 88 (84) plots respectively. Thus, mapping the latest AI_n for all districts would be useful because AI_n less than zero would signify which areas and their extent have the greatest chance of being below trend. Figures 4.3 through 4.6 are examples from the 2000 corn season. At week 14 (Figure 4.3), almost half the districts had overall weather, to that point, disadvantageous to the crop (negative AI_n). By week 18 (Figure 4.4), only a few districts with AI_{14} less than zero did not have cooler and wetter than normal weather to balance early impairments. Two new districts in NE became less than zero with the latest AI_n assessment at week 18. Week 22 (Figure 4.5) is a critical time and the raw AI is heavily weighted. Western NE continued to be arid and probably would be an area of concern, but AI_{22} in much of the southeast part of the region would begin to assure the area had a good chance of being above trend. The end of the season at week 27 (Figure 4.6) confirmed the usefulness of the one-to-one rule. There were 53 districts with AI_{27} greater than zero and above trend YLD, 18 districts with AI_{27} less than zero and below trend YLD, and only 14 districts (7 positive AI_{27} and 7 negative AI_{27}) that had YLD go against the sign of AI_{27}.

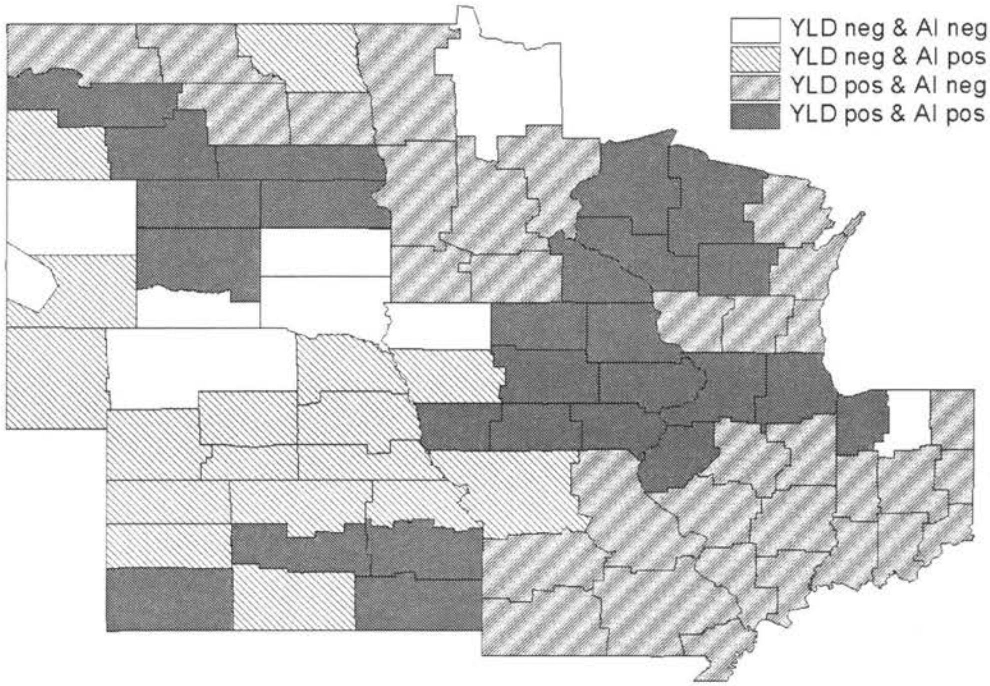


Figure 4.3 Combined signs (shading) of AI_{14} and the actual YLD, 5/31 - 6/6, 2000.

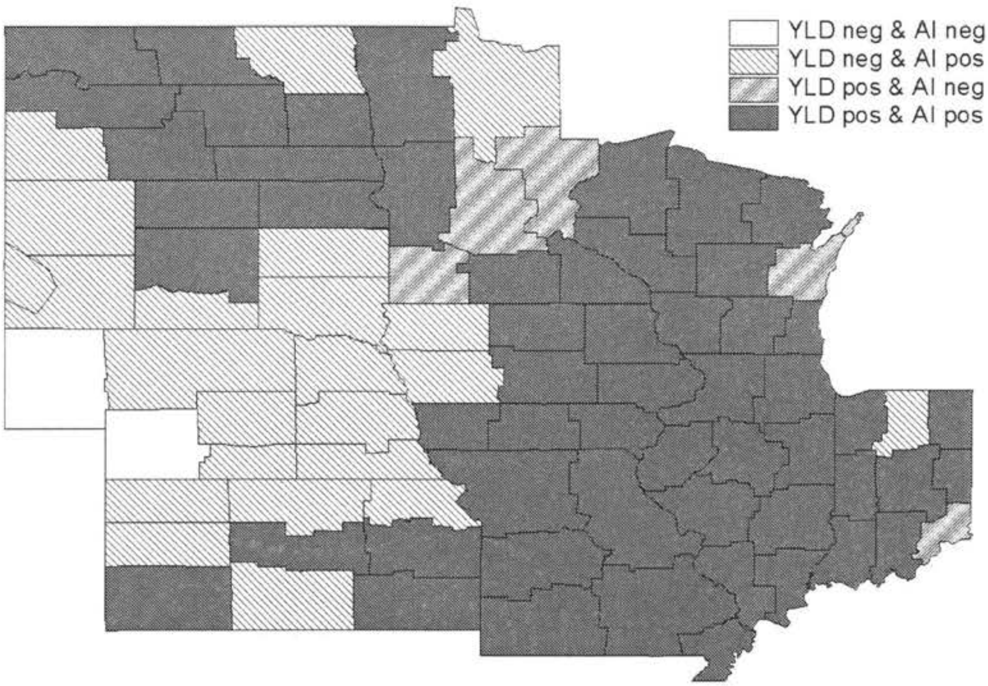


Figure 4.4 Same as Figure 4.3, but for AI_{18}, 6/28 - 7/4, 2000.

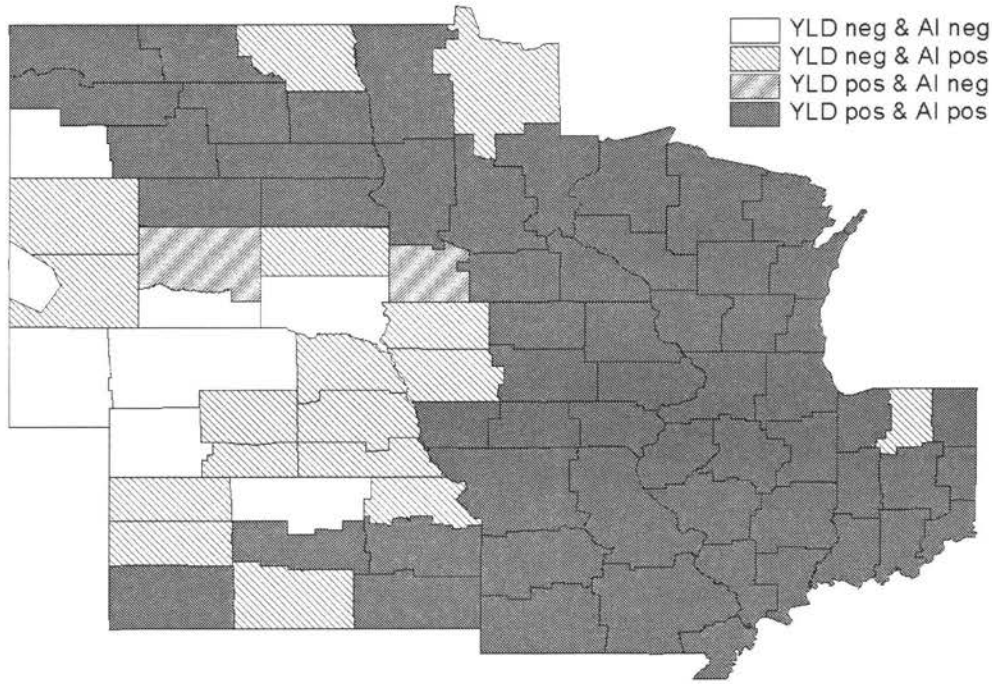


Figure 4.5 Same as Figure 4.3, but for AI_{22}, 7/26 - 8/1, 2000.

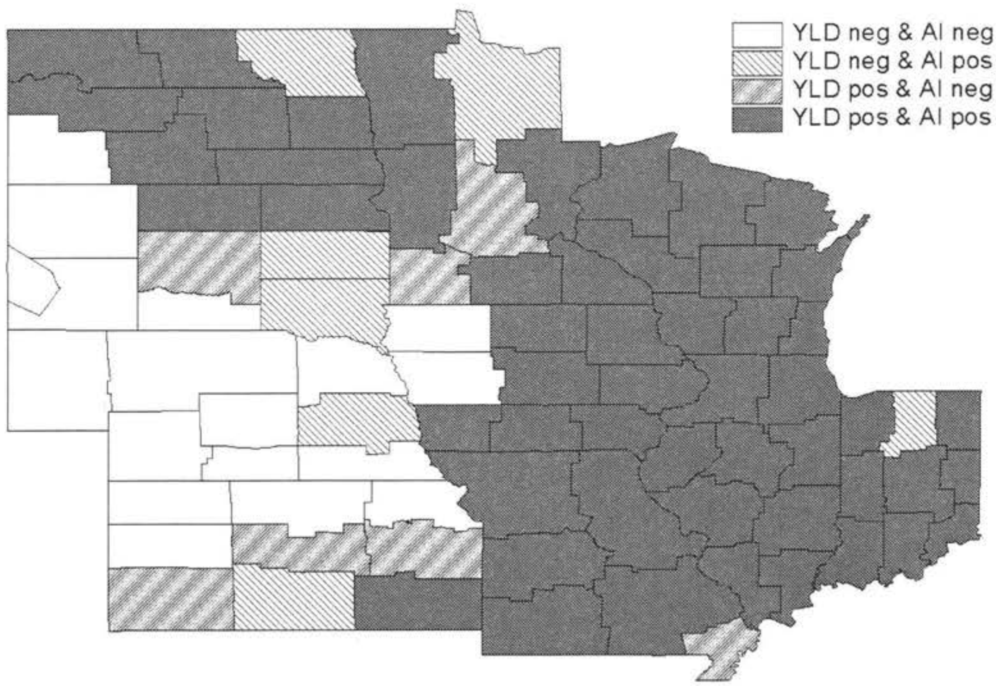


Figure 4.6 Same as Figure 4.3, but for AI_{27}, 8/30 - 9/5, 2000.

4.2 Testing Late Season Model Application on 2001 Growing Season

The same methodology that was used to test 2000 was applied to the 2001 season. Figure 4.7 again shows the seasonal AI, the modeled YLD for the eastern districts, and the actual YLD, but for 2001. According to seasonal AI, 2001 was generally warmer and drier than 2000. Again, the highly negative actual YLD generally correspond to the white and light gray areas (where seasonal AI was less than zero) while most of the darker gray districts (where seasonal AI was greater than zero) had positive YLD. Figure 4.8 shows the model error for the appropriate 2001 districts. There were several districts for which agreement was good between the modeled YLD and the actual YLD. Of these, many were grouped. One group included much of WI and extended into southeast MN and north central IA. Another group was northern IN and northeast IL. A pair of good estimates was hindcast for districts IA 7 and IA 8 with the model.

Three regions were areas of substantial underestimation. The first covered northwest WI and extended into central and northwest MN. The second area was composed of districts in eastern IA, northwest IL, and the southeast WI district (WI 9). Lastly, many of the southern IL and southern IN districts had underestimated YLD and were similar to the pattern seen for southern IL and southern IN for the 2000 application. In fact, the southern tier of IN districts was about 18-20% above trend in both 2000 and 2001. Figure 4.9 (http://www.usda.gov/nass/aggraphs/cornmap.htm) shows IN had a record yield of 156 bushels acre^{-1}, which was 10% more than the yield for the 2000 growing season. The large 2001 model error for the districts in southern IL and southern IN is not explained by the modeled YLD maximum because most of the seasonal AI values for these districts were not really in that range where the peak modeled YLD occurs. These districts just did really well under conditions slightly less cool and wet than the 2000 growing season. Out of 50 eastern districts, 24 had modeled YLD come within ±5 units of the actual YLD.

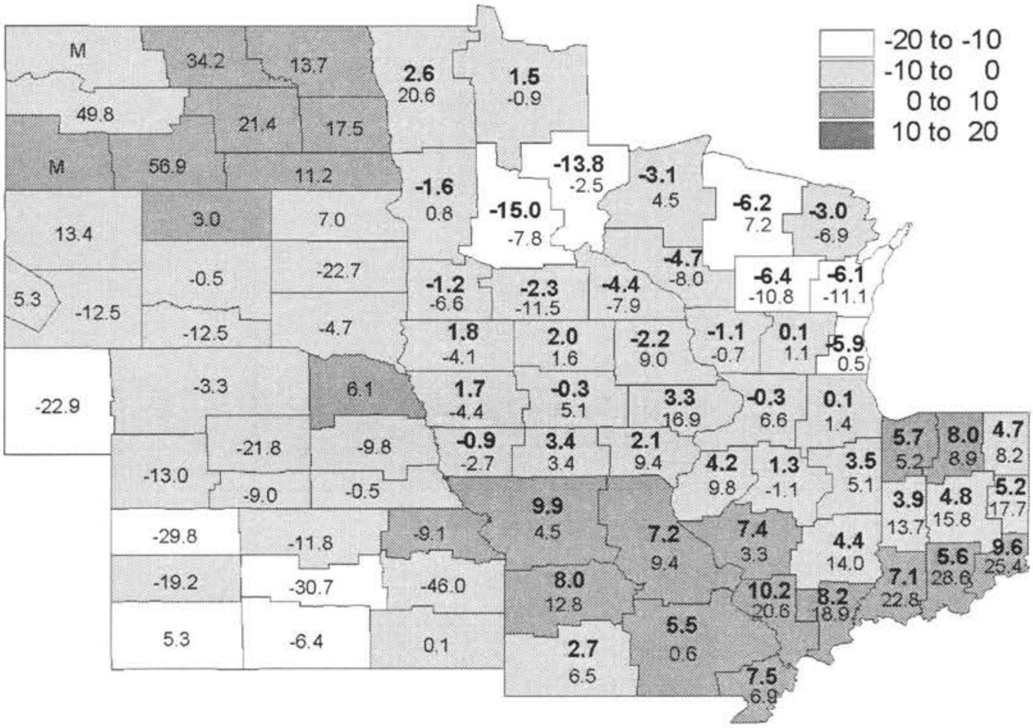


Figure 4.7 Same as Figure 4.1, but for 2001.

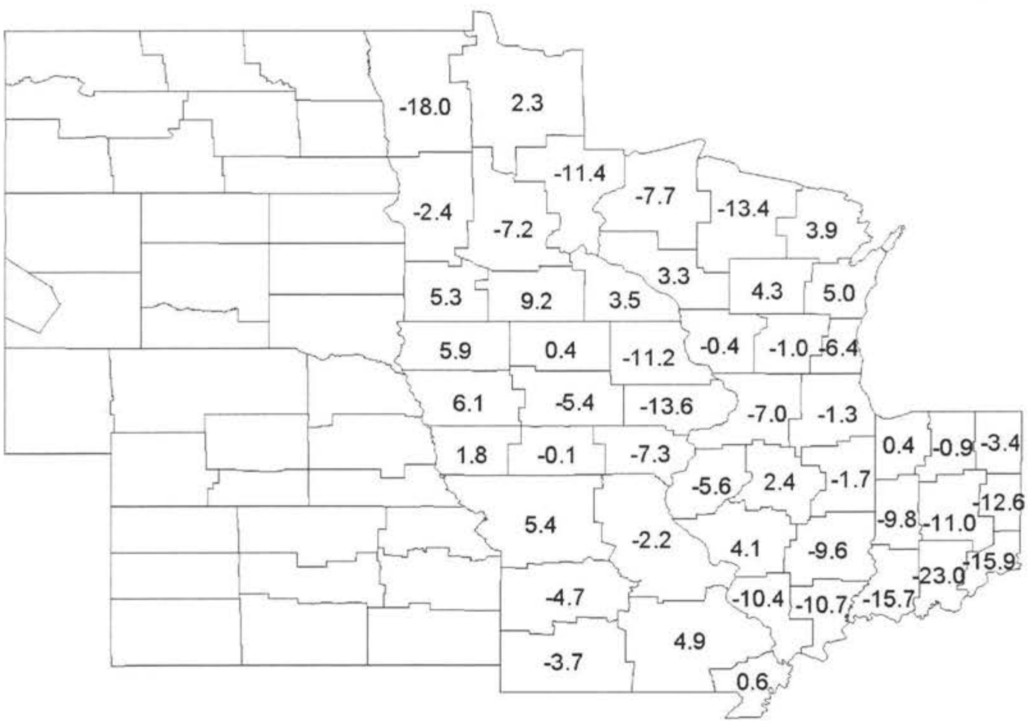


Figure 4.8 Same as Figure 4.2, but for 2001.

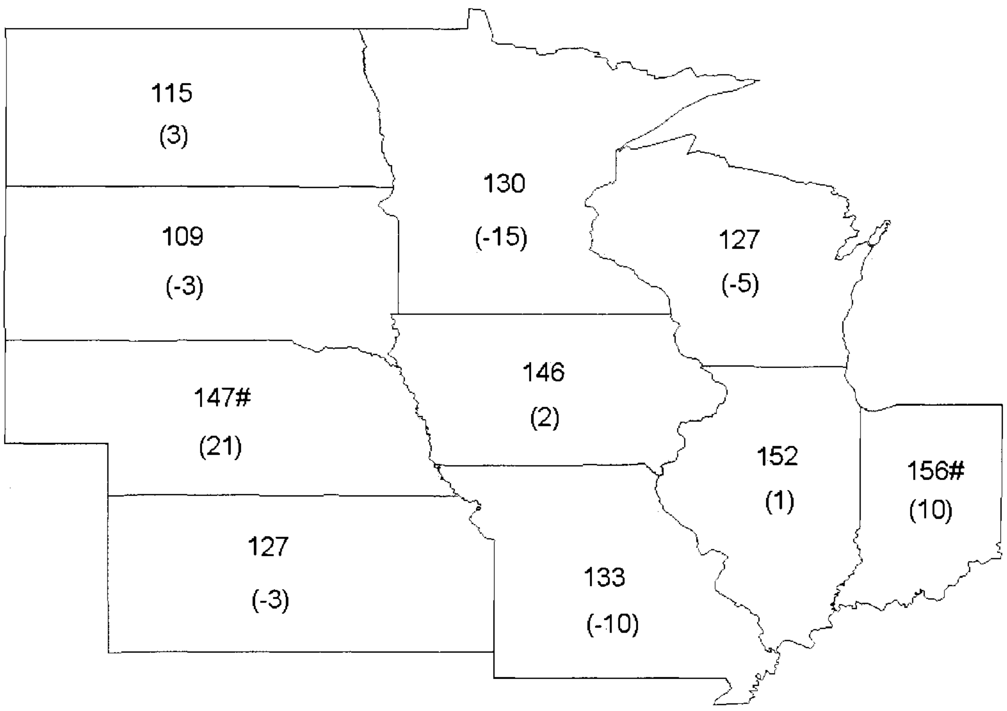


Figure 4.9 Corn grain yield per state for 2001. Total bushels acre^{-1} (top) and change from 2000 (bottom in parentheses). # indicates a record high. (Source: http://www.usda.gov/nass/aggraphs/cornmap.htm).

One of the districts with the largest error, WI 2, and its neighbor, WI 1, had AI_{27} and predicted YLD at levels comparable to surrounding districts, but had actual YLD above zero. The clearest reason for this is that these districts had a cool and wet week at a very good time (end of July; week 22). Figure 4.10 shows an AI_n sequential sample for district WI 2 and district WI 6. District WI 2 had a temporary AI_n peak at week 22 when the corn there was likely silking. District WI 2 ended the season with an AI_n about the same as district WI 6, but district WI 6 did not get the timely rain and, consequently, had an actual YLD well below zero. Other districts, such as WI 1 and WI 4 or IA 4 and IA 5, serve as additional examples of the occurrence and nonoccurrence of timely rain and the associated above trend yield and below trend yield respectively (not shown). For WI 1 and IA 5, AI_n jumped up at week 21 and week 25 respectively, which was likely responsible for their positive YLD though their seasonal AI was comparable to neighboring districts with negative YLD.

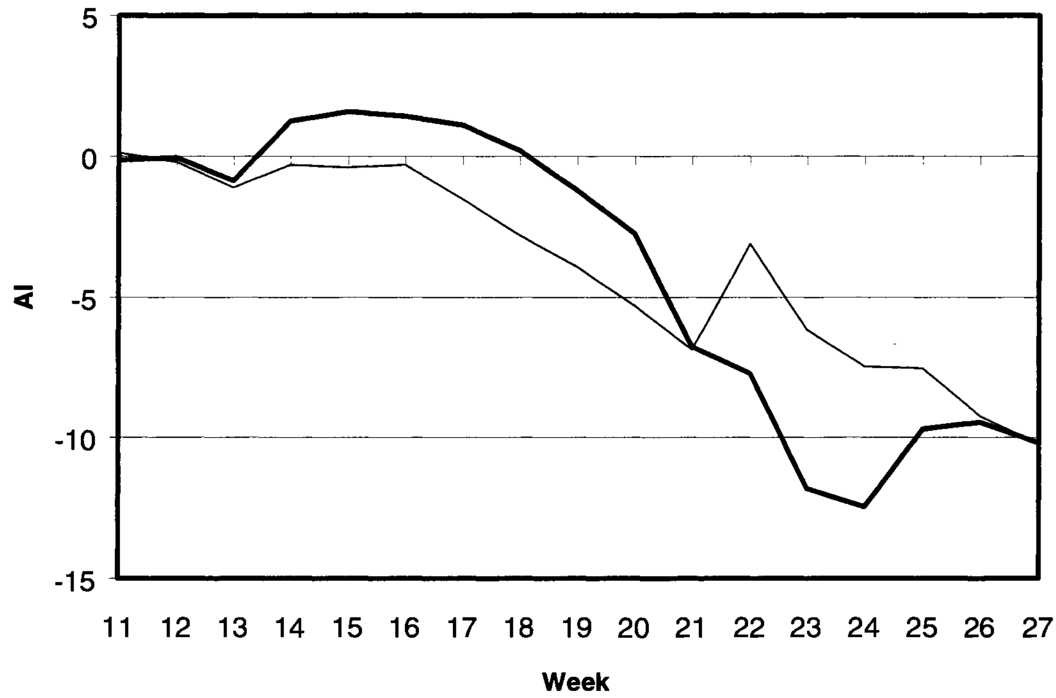


Figure 4.10 Sequential sample of 2001 AI_n for WI 2 (thin line) and WI 6 (heavy line).

As in 2000, a spatial and temporal assessment of AI_n in relation to the actual YLD was made for 2001. Figures 4.11 through 4.14 are examples from the 2001 season. At week 14 (Figure 4.11), the overall weather was cooler and wetter than usual in districts in northern WI and MN and district KS 7, which to that point was disadvantageous to the crop. By week 18 (Figure 4.12), regions with negative AI_n had spread into IA from MN and WI and into NE from southwest KS. If it was midseason and YLD was, of course, unknown, the centers of these regions may be areas where the chance of not making it to the trend value is increasing. Again, the raw AI was heavily weighted for week 22 (Figure 4.13) and the negative AI_n region expanded from the previous chart. Northern and western MN districts went above zero and so may have had a better chance of making it to trend. All of MO and IN, and districts in eastern ND start to look to have a good chance of being above trend. Upon comparison of the signs of AI_{27} and YLD (Figure 4.14), it was seen the one-to-one rule wasn't as strong for 2001 as it was for 2000. There were 21 districts with AI_{27} greater than zero and above trend YLD, 33 districts with AI_{27} less than zero and below trend YLD, and in 29 districts (1 positive AI_{27} and 28 negative AI_{27}) YLD went against the sign of the AI_{27}. Depending on the user, it is possible that the 28 districts with AI_{27} less than zero and YLD greater than zero were not a failure of the one-to-one rule. Some people may be pleasantly surprised to find that in 28 of these districts, the YLD was above trend even though they were perhaps not expecting it to be based on the one-to-one rule. On the other hand, some people would be disappointed only when considering the single district with negative YLD and an AI_{27} that ended on the positive side.

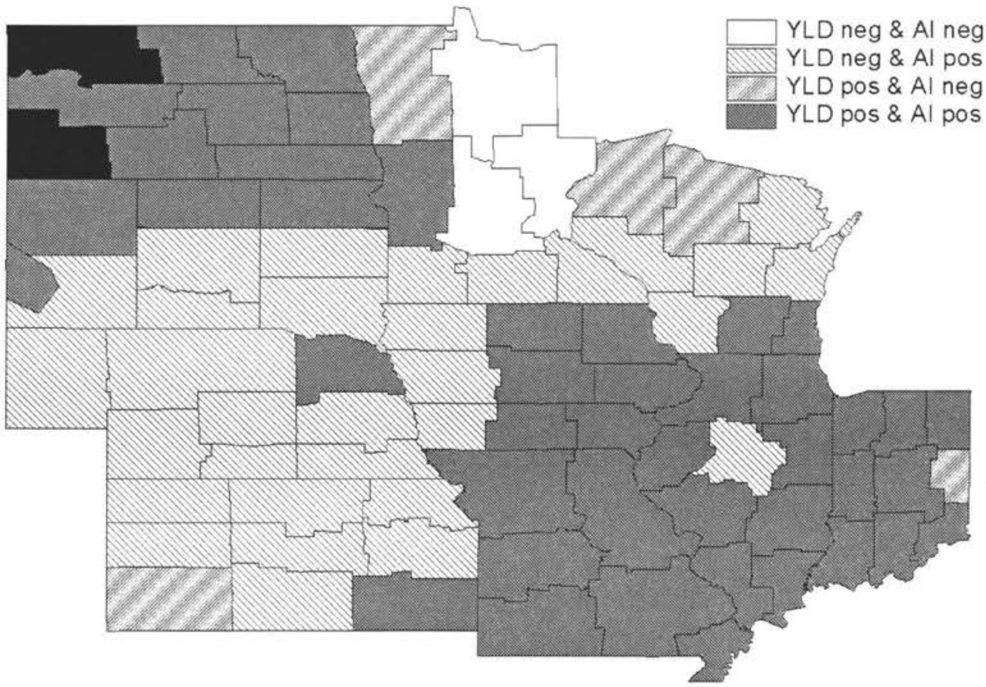


Figure 4.11 Same as Figure 4.3, but for AI_{14}, 5/31 - 6/6, 2001. Blackened districts in ND have missing YLD.

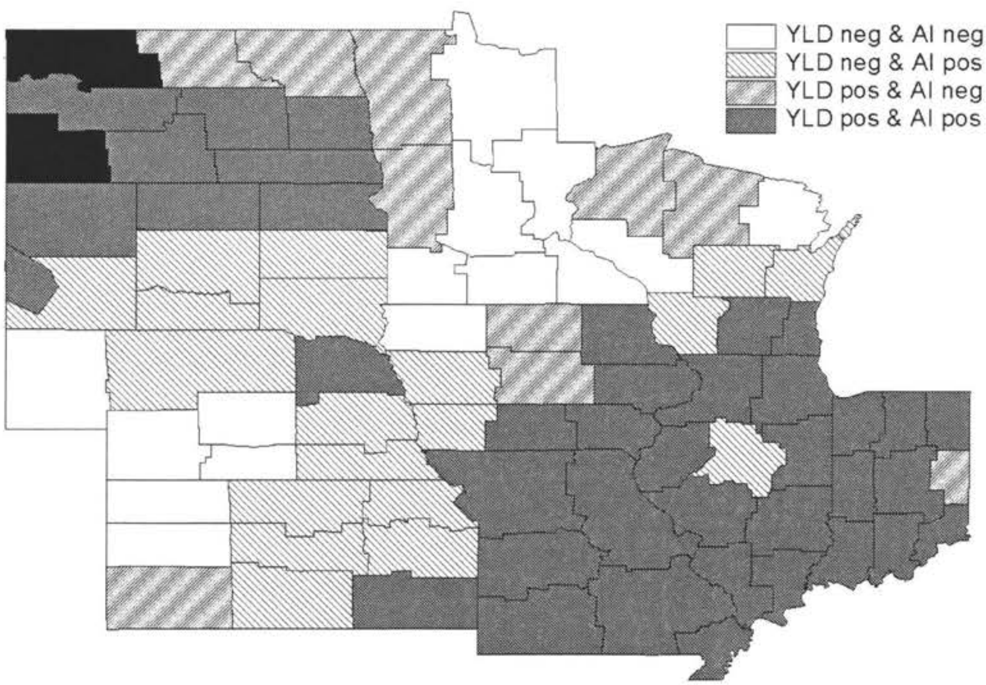


Figure 4.12 Same as Figure 4.11, but for AI_{18}, 6/28 - 7/4, 2001.

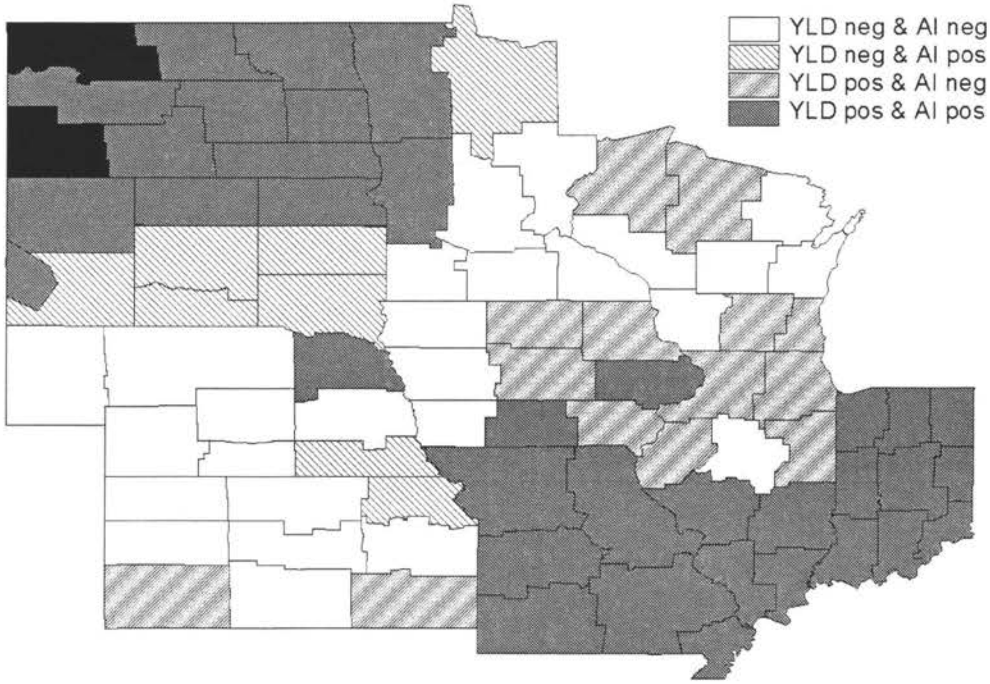


Figure 4.13 Same as Figure 4.11, but for AI_{22}, 7/26 - 8/1, 2001.

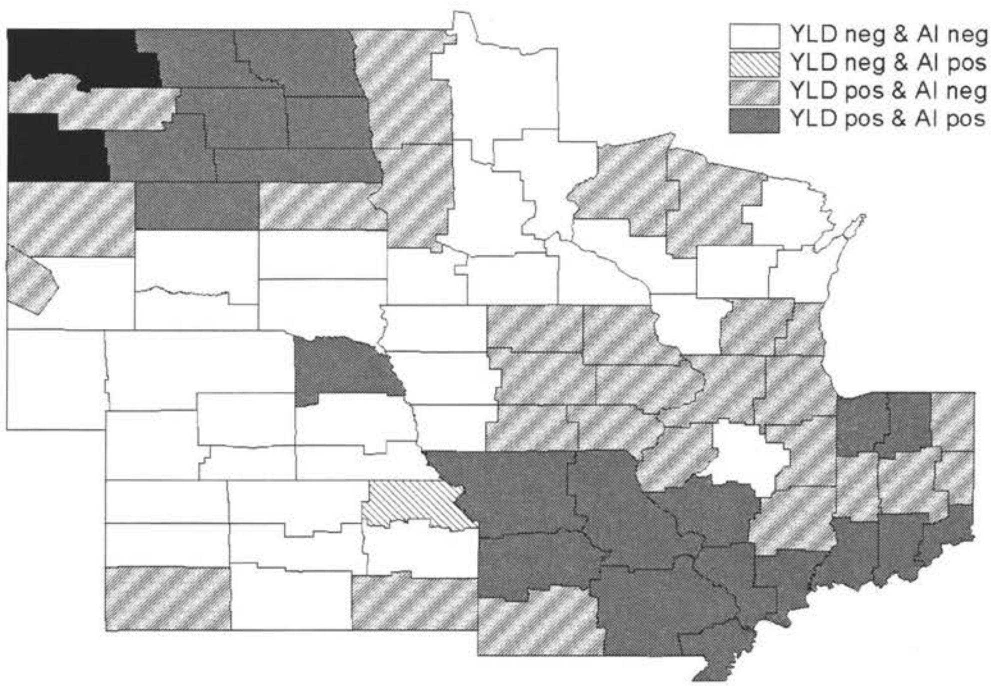


Figure 4.14 Same as Figure 4.11, but for AI_{27}, 8/30 - 9/5, 2001.

CHAPTER 5. DISCUSSION

For the 2000 and 2001 corn seasons, the results from using a second order multiple linear regression model were mixed, particularly for the peak of the model curve. It seemed easy for the model to overestimate YLD for a moderately wide range of AI_n. On the other hand, the peak modeled YLD sometimes fell quite short of the actual often because of the parabolic nature of the model.

5.1 Considering the Definition of AI

At this developmental stage of the AI method, the definition of AI was kept simple. The definition of AI used here was a special case of an expanded definition (Equation 5.1) that accounts for different contributions to "aridity" from precipitation and temperature at different times during the season.

$$AI_n = \sum_{i=11}^{n} k_i \,(a_i P'_i - b_i T'_i) \qquad (5.1)$$

On a monthly scale, precipitation in July is a bigger factor than temperature for YLD, but contributes less to YLD than temperature in August (Thompson 1986). Differing contributions to AI from precipitation and temperature on a weekly scale were beyond the scope of this study. When it was stated that precipitation and temperature were equal contributors to the weekly AI, it was assumed $a_i = b_i = 1$ for all weeks (i).

The corn phenology weighting factor (k_i) was also rigid. All weighting was applied with respect to having main silking occurring during climate week 21 and all weighting was applied to all districts equally. In IA, there is a good chance that silking will occur in or near week 21, but silking may happen at different times in other locations. To adjust weighting with each weekly processing of AI as conditions warrant, either timely observations of silking dates would need to be obtained or crop stage would need to be estimated with growing degree days. To improve the AI method, it is recommended that further work be done to find optimal corn phenology weighting and to incorporate it with the optimal contribution factors of precipitation and temperature.

Aside from weighting factors, there are other fundamental issues with the AI definition. One issue is the possibility of certain combinations of extreme weather weeks causing AI_n to be near neutral at any particular time. The extreme weather could quite likely result in a fairly large below trend YLD, but if opposite weather occurred for enough weeks, the resulting AI_n value would not indicate the drastic negative YLD. For example, if July was arid, and August was proportionally cool and wet, then AI_n would be near zero, but the crop would have performed poorly because of the July conditions. The method, as it stands now, allows AI_n to move back toward zero even though irreversible yield loss may have occurred. In other words, the crop's ability to recover from aridity or flood is quite limited, but the AI method does not account for this limitation.

Another consideration in regard to the defining equation of AI is the possibility of AI being near zero when a week's weather is wet and warm or cool and dry. It was assumed that these conditions would have approximately the same effects as average conditions. "Warm" would indicate higher transpiration, but "wet" would mean precipitation would be sufficient to sustain the higher water usage. Similarly, "cool" would indicate lower transpiration, so "no rain" would not be harmful.

Finally, normalizing a precipitation distribution that is not normal does not promote symmetry between the possible positive and negative values of the P' term. For example, a positive P' value can be very high, but a negative P' value can only go so low because a district's average weekly precipitation cannot go below zero. Instead of normalizing precipitation to calculate P', perhaps the P' term would be more consistent with some sort of percentile scheme. One idea is presented in Equation 5.2.

$$P' = 5 * (\text{Percentile of } P - 0.5) \tag{5.2}$$

If a district's weekly average precipitation (P) was at the 10^{th} percentile, P' would be 5*(-0.4) or –2.0.

Further refinement might be necessary for the value to better agree with ±2 standard deviations containing 95% of a normal distribution.

5.2 A Possible Alternate Model

Flooding had a large influence on the shape of the parabolic model. Too much water is harmful to the crop, so YLD could be largely negative when AI_n was largely positive. If a distinction were made between flooding and no flooding when AI_n was high, such that the model excluded flooding situations, it would have a smaller tendency to underestimate YLD. Although underestimation is inherent near the peak of the parabolic model, excluding flood situations would shift the peak such that the model would better represent crops that were not flooded. From a physical point of view, excluding flood situations would nullify the quadratic relationship of YLD to seasonal AI. If many of the plots from the lower right quadrant in Figure 3.1a were justifiably eliminated, the relationship of YLD to AI_{27} would look quite linear. A logical next step then is to account for flooding and use a linear regression model or combinations of linear regression models. A single order linear model would not have the problem of underestimating YLD because of having some possible maximum value, as did the quadratic model used in this study. Figure 5.1 illustrates how the quadratic model often underestimated YLD. The maximum modeled YLD is evident because no values are above about +11 units. Using a linear model for the 2000 and 2001 seasons would likely bring more of the plots on the right side of the chart inside the ±5 unit interval.

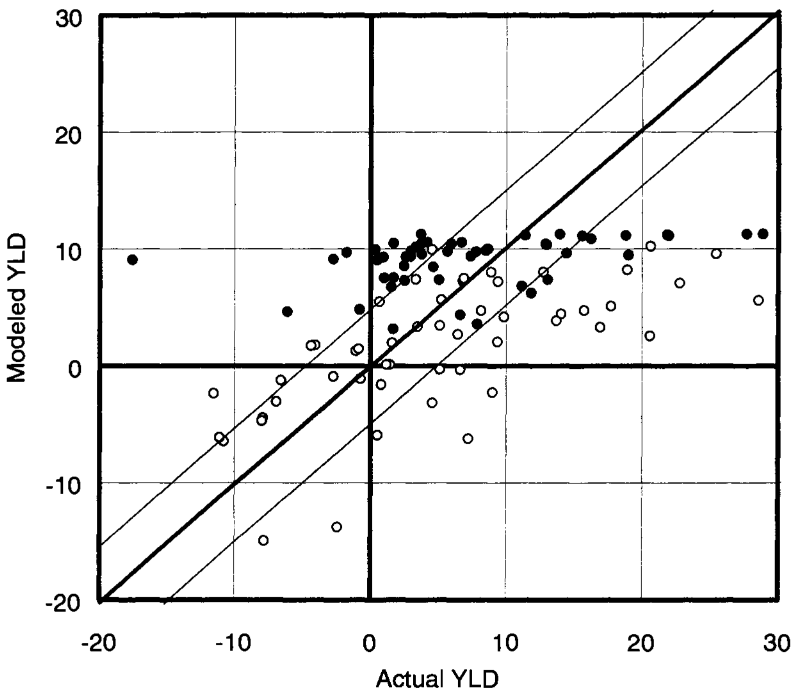


Figure 5.1 Comparison of actual YLD and modeled YLD for 2000 (filled circles) and for 2001 (unfilled circles). Heavy diagonal line is zero model error and thin diagonal lines are ± 5 unit model error.

5.3 Other Error Sources

There are other possible sources of error. For high aridity, irrigated corn may do well and keep the total yield relatively higher even though AI_n is quite low. Thus, the total yield in the eastern states may have contributions from irrigated corn, which may have influenced the yield deviation used here for the eastern states. Other issues besides irrigation may be factors. Meyer et al. (1993a) acknowledge soil quality, hybrid type, and damaging elements, such as insects, disease, hail, and wind, impact yield and may be sources of error. Thompson (1986) studied the effects of climate change on the upward trend in corn yield, and thus had to separate the influence of weather from the influence of greater fertilization, improved genetics, improved pest control, and improved management.

CHAPTER 6. GENERAL CONCLUSIONS

6.1 Summary

For a growing season, a method to judge whether a week's average maximum temperature and average precipitation were helpful or harmful to the season-end corn yield was presented. Hindcasting was done on the 2000 and 2001 corn growing seasons with mixed results. Of the modeled YLD for 2000 and 2001, about 45% of the predictions for the districts came within ±5 units of the actual YLD. For most weeks, the chance of an eastern states' district having positive YLD diminished as AI_n went below certain values and was significantly better than the unconditional chance when AI_n went above certain values. Operationally, a model that predicts yield to ±10 % is considered acceptable and to ±5 % is excellent. On this basis, this model is of value because it is reasonably accurate and is simple to implement on a week-by-week basis. When this (AI) model shows cause for concern, a user may desire to invest effort in a more detailed assessment.

During the 2-year evaluation (2000-2001), the model accuracy for the period improved as the season progressed. On June 6, the model correctly classified 47 percent of the crop-reporting districts in the Corn Belt. On July 4, 60 percent were correctly classified. After August 1, the accuracy of classification was 75 percent. Because both years had yields very near the long-term trend, this is considered a very good result. The AI model also performed well under worst-case considerations. That is, it did not predict a substantial number of above-trend yields that proved to be under the trend.

6.2 Discussion of Making the AI System Operational

For upcoming growing seasons, two main items should allow for meaningful dissemination of AI information (primarily via the World Wide Web). Maps of district AI_n will display the spatial extent of warmer and drier or cooler and wetter than average weather. The other important item will be a sequential sample for each district. Because there are 85 districts in the Midwest, it would be awkward to produce 85 time series charts each week. An alternative would be to set up the map so each district has a link to an automatically generated chart.

Examples from the end of the 2000 and 2001 season are available along with an operational 2002 product (http://www.mesonet.agron.iastate.edu/~windmill/AIpage.html). As in these examples, the AI product for upcoming seasons could include appropriate charts and tables, which would allow users to make decisions based on their own assessment of the historical relationship.

6.3 Future Work

The AI method has potential for improvement. First, the raw weekly AI could be refined by dealing with the P' term differently and by considering how much each term is contributing at what points in the growing season. The next adjustment would be a more realistic crop phenology weighting scheme. After these steps, the seasonal AI should again be plotted against YLD, but perhaps without YLD influenced by flooding, such that a linear model might be appropriate. Even if the relationship does not prove to be more consistent after the changes, AI results should still be compared to results from previous studies such as the ones authored by Shaw (1983), Thompson (1986), Harouna and Carlson (1994), and Meyer et al. (1993), which were discussed in Chapter 1. Such comparisons would help better determine the value of the AI methodology.

The AI methodology could include an incorporation of operational long-range weather forecasts to project the summer's possible AI tendencies. A shorter term AI forecast, especially the precipitation component, might be made based on the trend of the low-level flow from the Gulf of

Mexico. If the AI method proves to be successful, it would be natural to extend it to soybeans and other crops. It could also be extended beyond the Midwest. Eventually extrapolation from the 1980 to 1999 yield trend would need to be reevaluated because the upward trend of yield due to technology will likely level off. Averages used to normalize temperature may also have to be reevaluated to match the current climate with the appropriate past climate.

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